Evaluating the Effect of Changes in Flow and Water Temperature on Stream Habitats and Communities in the Los Angeles/Ventura Region Conceptual Approach and Summary of Available Data





Eric D. Stein Jenny Taylor Ashmita Sengupta Sarah M. Yarnell

Southern California Coastal Water Research Project SCCWRP Technical Report 1034

Evaluating the Effect of Changes in Flow and Water Temperature on Stream Habitats and Communities in the Los Angeles/Ventura Region: Conceptual Approach and Summary of Available Data

Eric D. Stein¹, Jenny Taylor¹, Ashmita Sengupta^{1,3}, and Sarah M. Yarnell² ¹Southern California Coastal Water Research Project ²University of California, Davis, Center for Watershed Sciences ³Current address: Commonwealth Scientific and Industrial Research Organization, Canberra, Australia

ACKNOWLEDGEMENTS

We thank the members of our technical advisory committee, who have provided valuable guidance based on their expertise in stream ecology, the native stream vertebrates, and the environmental conditions that support them. In addition to providing ongoing technical guidance, the following individuals have also contributed datasets that are vital for our modeling and data analysis: Jennifer Pareti, Rosi Dagit, Mary Larson, Kyle Evans, and Chris Medak. We thank Celine Gallon and Deborah Smith of the Los Angeles Regional Water Quality Control Board for their input on this project's concept and methodology.

Technical Advisory Committee

Stacey Osterman, National Park Service Katy Delany, National Park Service Anke Mueller, United States Geological Survey Mary Larson, California Department of Fish and Wildlife Kyle Evans, California Department of Fish and Wildlife Kelly Schmoker, California Department of Fish and Wildlife Jennifer Pareti, California Department of Fish and Wildlife Robert Holmes, California Department of Fish and Wildlife Jason Hwan, California Department of Fish and Wildlife Erinn Wilson, California Department of Fish and Wildlife Andrew Valand, California Department of Fish and Wildlife Jack Simes, United States Bureau of Reclamation Nathan Holste, United States Bureau of Reclamation Doug McPherson, United States Bureau of Reclamation Jennifer Mongolo, County of Los Angeles Department of Regional Planning Jessica Bean, State Water Resources Control Board Rosi Dagit, Research Conservation District of the Santa Monica Mountains Sabrina Drill, University of California Extension Nathan Sill, United States Forest Services Chris Medak, United States Fish and Wildlife Service

PREFACE

This document provides the conceptual foundation and background material for a project conceptualized and funded by the Los Angeles Regional Water Quality Control Board. The project aims to investigate how climate change-induced alterations in precipitation and temperature may influence the distribution of riparian-dependent species within this region. The outcome will be used to inform decisions about protection and management of streams within the Los Angeles Regional Board's boundaries (i.e., the study area). This document includes a compilation of riparian-dependent species known to occur in the study area, an approach for organizing and prioritizing species for analysis of climate change effects, and an overview of potential modeling approaches. Note that this is a planning and background document that provides progress to date, and all sections will likely be modified as this project progresses.

TABLE OF CONTENTS

Acknowledgements	i
Preface	. ii
Introduction and Objectives	.1
Regional Riparian Species and Approach for Selecting the Species to be Modeled	.2
Ecologically and recreationally important aquatic taxa in the Los Angeles region	.2
Overview of datasets	.6
Selection of focal species to model1	11
Overview of Modeling Methods to Assess Ecological Effects of Flow Changes1	12
Considerations for model selection1	16
Spatial and temporal specificity of model output1	16
Species vs. community level responses1	17
Availability of data1	8
Model selection flow charts2	21
General consideration of flow and temperature requirements2	24
Functional flow metrics2	25
Next Steps2	27
Literature Cited	29
Appendices	34

INTRODUCTION AND OBJECTIVES

Flow regime changes have been shown to affect a broad suite of ecological processes and biological communities (Bunn and Arthington 2002, Naiman et al. 2002, Poff and Zimmerman 2010, Novak et al. 2015). Much of the worldwide focus on assessing ecological effects of hydrologic change has been focused on long-standing human activities that can affect flow, such as conversion of natural lands to urban or agricultural landscapes, infrastructure development, and water management through dams and diversions. These activities alter the flow regime through changes in flow magnitude, duration, timing, frequency, and rate of change (Poff et al. 1997).

In addition to direct human impacts on waterways, there is a growing recognition of the impact of global climate change on stream flow. These changes impact the relative abundance of species globally (McLaughlin et al. 2002) by altering the extent and condition of habitat necessary to support aquatic biodiversity (Jetz et al. 2007, Bellard et al. 2012). When aquatic species experience a change in hydraulic regime or water temperature, it is likely that specialist species (often natives) will lose out to other more generalist (often exotic) species. This was shown by Poloczanska et al. (2008) with a two-taxa population model and climate envelop model, which were used to investigate the responses of populations of competing species to climate change. Poloczanska et al. (2008) noted the complete extinction of one taxa and a rapid increase in the second taxa under future climate scenarios.

For species that rely on freshwater aquatic habitats for all or part of their life cycles, climate change may degrade needed aquatic habitat through changes in seasonal or annual temperature, increases in extreme heat events, changing precipitation patterns (including the proportion of snow vs. rain), and subsequent magnitude and timing of runoff and sediment yield. These changes cumulatively impact channel morphology and water temperature, which ultimately harm aquatic dependent species (Figure 1).



Figure 1: Anticipated impact of climate change on biological endpoints due to flow and temperature changes.

The freshwater habitat impacts of these climatic changes are difficult to assess and model in general, and especially in regions like Southern California with complex topography that creates microclimates that may result in complex localized responses. However, recent efforts to downscale global climate change prediction (ca. 2100) to high spatial resolution projections for the greater Los Angeles region provide a unique opportunity to explore the impacts of climate change on aquatic species important to the ecology of the region. Using these downscaled climate predictions, we can model riverine systems to begin to understand how streamflow will

be impacted and, more importantly, whether these changes in streamflow will put sensitive aquatic species at increased risk of population decline.

Working with the Los Angeles Regional Water Quality Control Board, we propose to *develop a framework for relating climate change-induced alterations in streamflow to changes in key ecologically and recreationally important biological communities.* This work will augment past efforts to develop assessment tools for benthic invertebrates by focusing on development of tools for higher-level taxa, such as fish, amphibians, birds, and/or riparian communities. This document serves as a first step in this process. In this document, we:

- 1) summarize the ecologically and recreationally important aquatic communities known to occur in the Los Angeles Regional Board's jurisdiction
- 2) outline a process for prioritizing which communities should be the focus of analysis of climate change effects
- 3) summarize available modeling approaches to relate changes in temperature, flow and physical habitat to changes in habitat suitability or the likelihood of occurrence of priority biological communities
- 4) evaluate the strengths and limitations of available modeling tools at helping to achieve the overall project objective

REGIONAL RIPARIAN SPECIES AND APPROACH FOR SELECTING THE SPECIES TO BE MODELED

Ecologically and recreationally important aquatic taxa in the Los Angeles region

The Los Angeles Regional Water Board region covers approximately 4083 sq. miles with 25% mountains, 10% coastal plains, and 65% foothills, valley or desert. There are six principal hydrologic units: Ventura, Santa Clara, Calleguas, Los Angeles, San Gabriel, and Santa Monica Bay (Figure 2). The principal vegetative cover of the upper mountain areas is bush and shrubs categorized as chaparral. Alder, willow and sycamore are found along the streambed at lower elevations.



Figure 2: Map of the study area

We identified 66 riverine- or riparian-dwelling species, which include seven recreationally important fish species that are known to occur in the Los Angeles Region (Appendix A). Seventeen of these species are currently considered sensitive (rare, threatened or endangered) under state or federal programs (Table 1). To qualify for inclusion, a species needed to be at least partially dependent on the instream or riparian habitat, like the Great Blue Heron, or fully dependent, like the American Dipper. Species that primarily use other types of aquatic habitats, like estuaries or lakes, but not streams, are not included for this analysis. Figures 3-6 show maps representing general locations of riparian species occurrence from Global Biodiversity Information Facility (GBIF.org) and The Nature Conservancy (TNC) California freshwater species database, version 2.0.7. Note that these maps reflect our initial exploration and are not updated with the species occurrence data being used in this project (Table 2) because the data were still being compiled and cleaned as of the publication of this document. As such, please note that some species such as southern California steelhead are not represented, and other species are severely underrepresented, such as the Santa Ana sucker in the San Gabriel watershed.

Table 1: Summary of species included in this project. For complete list of species, refer to Appendix A.

Taxa Group	Number	Sensitive	Native
Reptile	6	0	2
Amphibian	10	5	9
Bird	31	6	31
Fish	19	5	5
Totals	66	16	47



Figure 3: Amphibian presence.



Figure 4: Reptile presence.



Figure 5: Fish presence.



Figure 6: Bird presence.

Overview of datasets

For building the species distribution model, species occurrence data is being compiled, digitized (when necessary), and cleaned from raw survey data or published reports from surveys. The dates used in the datasets are from 1980 through present because that is the time period for which we have the precipitation time series for the region and will model the hydrology. We will be using the survey data from experienced biologists which are more reliable both for species identification and absence as opposed to citizen science data, which lack reliable absence information and are biased in favor of where people tend to hike and recreate. However, even with standard surveys completed by experts, it is always possible that a species occurrence was missed; thus, absenses should always be treated with caution regardless of the source. In these surveys, species occurrence are noted with total count or presence/absence. Occasionally, the survey length is also recorded in which case species abundance (count per stream length) can be calculated by dividing the total count by the stream segment surveyed.

Stream-dependent species were relatively evenly distributed across the six major watersheds in the region, and there were data available in headwater streams, mainstems, and lower reaches into the estuary. See Table 2 for an overview of the datasets compiled thus far and currently being assembled into a species occurrence master database.

Table 2: Sources with species occurrence records by watershed showing the date of survey or observation, stream, main species, and source. The data from these sources are being digitized if needed (converted from report format to a dataset that can be used in modeling) to create a master dataset of reliable species occurrence data of the focal species. Note the last section is 'All Watersheds' meaning the sources listed contain a compilation of observations spanning multiple watersheds in the study region.

SURVEY DATE	STREAMS	MAIN SPECIES	SOURCE
SANTA CLARA WA	TERSHED		
2016-2017	Sisar Creek, Santa Paula Creek	steelhead, California red-legged frog, two-striped garter snake, western pond turtle	California Dept. of Fish and Game
1983-1985	Sespe Creek: Bear Creek, Hot Springs Canyon	rainbow trout, arroyo chub, unarmored threespine stickleback, green sunfish, pacific lamprey	California Wild Trout Management Program. Sespe Creek Wild Trout Management Plan, Sespe Creek, Ventura County. CGFG, 1986
1995	Santa Clara River and San Francisquito creek	unarmored threespine stickleback, arroyo chub, Santa Ana sucker, arroyo toad, California red-legged frog, western spadefoot, western pond turtle, two- striped garter snake	Sensitive Aquatic Species Survey Santa Clara River and San Francisquito Creek. Newhall Land and Farming Company Property. Los Angeles County, CA. Haglund & Baskin, 1995
1992-1997	Santa Clara River at Newhall Land and Farming Crossings	unarmored threespine stickleback, arroyo chub, Santa Ana sucker, California red-legged frog, western pond turtle, two-striped garter snake	Habitat Conservation Plan for the Federally Endangered Unarmored Threespine Stickleback and other Species of Special Concern at the Newhall land and Farming Company's Crossings of the Santa Clara River, Los Angeles and Ventura Counties, CA. Haglund & Baskin, 2004
2000	Santa Clara River at Interstate 5	unarmored threespine stickleback, arroyo chub, Santa Ana sucker, least bell's vireo, southwestern willow flycatcher, San Diego horned lizard (other species and plants recorded)	Fish and Wildlife Survey and Habitat Assessment of the SCR at Interstate 5, Haglund & Baskin, 2000
2002	Santa Clara River Newhall Ranch area	unarmored threespine stickleback, arroyo chub, and Santa Ana sucker (additionally: prickly sculpin, mosquito fish, largemouth bass, western pond turtle, African clawed frog)	Results of Focused Surveys for unarmored threespine stickleback and other special status fish species. Newhall Ranch, Valencia, CA. Impact sciences, Inc, 2003

2007-2010	Santa Clara River and tributaries	unarmored threespine stickleback, arroyo chub, Santa Ana sucker	San Marino Environmental Associates - no title page
2008	Fish Creek and Agua Blanca Creek	coastal rainbow trout, Santa Ana sucker, Santa Ana speckled dace	Fish Creek and Agua Blanca Creek Summary Report June 16-19, 2008. Dept. of Fish and Game. Heritage and Wild Trout Program. Weaver & Mehalick, 2008
2008	Snowy, Buck, Piru, Alamo, Mutau Creek	coastal rainbow trout, Santa Ana sucker, Santa Ana speckled dace	Upper Piru Creek Summary Report. Snowy, Buck, Piru, Alamo, and Mutau Creeks, June 11-13, 2008. Dept. of Fish and Game. Heritage and Wild Trout Program. Weaver & Mehalick, 2008
2005-2006	Santa Clara River, Aliso, Escondido, lower Sespe, and Santa Paula Creeks	Pacific chorus frog, California chorus frog, California red-legged frog, western spadefoot, arroyo toad, California toad, African clawed frog, bullfrog	SCR Watershed Amphibian and Benthic Macroinvertebrate Bioassessment project, Hovore et al. 2008
1994	Santa Clara River	Western pond turtle	San Marino Environmental Associate Southwestern Pond Turtle data, ARCO natural Resource Damage Assessment. 1994
2005-2006	Many	Bird species (many)	Avian Populations on the SCR in 2005 and 2006. An Evaluation and Monitoring Tool for Habitat Restoration Ventura County and LA County, California, 2011 Labinger, Greaves, Gevirtz
2014	Santa Clara River	Bird species (many)	Results of Bird Surveys on Nature Conservancy Properties Along the Santa Clara River, Ventura County, California
1999-2006	Santa Clara River and tributaries in Newhall ranch area	Bird species (many)	Bird Surveys on the SCR through 1980's - 2006, D.A. Guthrie
1994-1996	Agua Dulce tributary to SCR	unarmored threespine stickleback, arroyo chub	Status and Monitoring of the Agua Dulce UTS Population. Haglund & Baskin. 1996
2005	Santa Clara River mainstem by Interstate 5	Arroyo toad	2005 Arroyo Toad Surveys at the Interstate 5 Bridge Construction Site. San Marino Environmental Associates.
2005	Castaic Creek, San Francisquito Creek	Santa Ana sucker, arroyo chub, silversides, unarmored threespine stickleback	SMEA memorandums for Tapia Canyon Road and Tesoro Stickleback survey

SAN GABRIEL WAT	ERSHED		
2007-2008	San Gabriel River north fork, east fork, west fork mainstems, and many creeks	Santa Ana sucker, Santa Ana speckled dace, arroyo chub, rainbow trout	Status of fishes in the Upper San Gabriel River Basin, Los Angeles County, CA, Obrien, Hansen and Stephens, 2011
2009	East fork San Gabriel river, iron fork, fish fork	rainbow trout	East Fork San Gabriel River 2009 Summary Report. Dept. of Fish and Game. Heritage and Wild Trout Program. Weaver & Mehalick, 2009
2010	East fork San Gabriel river and Vincent gulch	coastal rainbow trout, Santa Ana sucker, Santa Ana speckled dace	East Fork San Gabriel River 2010 Summary Report. Dept. of Fish and Game. Heritage and Wild Trout Program. Weaver & Mehalick, 2010
SANTA MONICA MO	UNTAINS		
2009	Multiple streams and ponds in Santa Monica Mountain region	Western pond turtle	Distribution and Abundance of Western Pond Turtles <i>Actinemys marmorata</i> in the Santa Monica Mountains, Dagit and Albers, 2009
2008-2016	Topanga creek	Steelhead	RCD of the Santa Monica Mountains
2001-2017	Arroyo Sequit, Big Sycamore, Las Flores, Malibu, Solstice, Topanga, Trancas, Zuma, San Juan Creek	Steelhead, tidewater goby	RCD of the Santa Monica Mountains

LOS ANGELES RIVER

2015	Upstream of Sepulveda dam on Los Angeles River	tilapia, gambusia, shiner, clams, crayfish	Sepulveda Dam-LA River Fish Survey for FOLAR 2015. Hofflander & Dagit, 2015
2016	Upstream of Sepulveda dam on Los Angeles River	tilapia, gambusia, Atlantic clams, crayfish, Plecostomus, fathead minnow	Sepulveda Dam-LA River Fish Survey for FOLAR 2016. Dagit, 2016
2014-2015	Los Angeles river by the mouth in Long Beach	mosquitofish, fathead minnow, smelt, carp, stripped mullet, northern anchovies, California killifish, suckermouth catfish	FOLAR State of the River, the Long Beach Fish Study, 2016

2009-2014	Big Tujunga creek	Santa Ana sucker, incidental captures of arroyo chub and Santa Ana speckled dace	Santa Ana Sucker Habitat Suitability Survey Results and 6th Annual Santa Ana Sucker and Benthic Macroinvertebrate Survey Results. Big Tujunga Creek, Los Angeles County, CA, 2015
2006	Big Tujunga creek and three small side channels	Santa Ana sucker, arroyo chub, Santa Ana speckled dace	SMEA Memorandum for Big Tujunga Wash Project, 2006
2012/2013	Big Tujunga Dam and Reservoir section/ Arroyo Seco	Least Bell's vireo, Southwestern willow flycatcher, and other native species	BonTerra Consulting survey reports, 2012 and 2013
2010	Big Tujunga Wash at Oro Vista Avenue	Arroyo chub, Santa Ana sucker, Santa Ana speckled dace	ECORP Consulting, Inc. Report for the Santa Ana Sucker (<i>Catostomus santaanae</i>) Survey and Relocation Effort in the Big Tujunga Wash at Oro Vista Avenue (W.O. E1907366). Prepared for the City of Los Angeles. 2010.
VENTURA RIVER			
2013-2017	San Antonio Creek, Ventura River, Lion Creek, North Fork Matilija Creek, Upper Matilija Creek, Upper North Fork Matilija Creek, Bear Creek	Steelhead, California red-legged frog, two-striped garter, western pond turtle	California Dept. of Fish and Game
ALL WATERSHEDS			
HISTORICAL - 2014	Multiple	Multiple species database	TNC California Freshwater Species Database, Version 2.0.7
1991-2005	Multiple	Multiple species database	U.S. Fish and Wildlife fish surveys
HISTORICAL-2017	Multiple	Multiple species database	Occurrence Information for Multiple Species within Jurisdiction of the Carlsbad Fish and Wildlife Office (CFWO). U.S. Fish and Wildlife Service, Carlsbad Fish and Wildlife Office.

Selection of focal species to model

Assessing ecological flow needs for all riparian species is challenging due to differences in the availability of flow-ecology data between species. However, because many species have overlapping habitat requirements, focal species can be analyzed, and the results extrapolated to species with similar habitat and flow needs. We used a two-step process to determine which focal species should be prioritized for analysis of climate change effects.

During the first step, general habitat requirements throughout the life history of all documented riparian species were assembled based on literature searches, reports, and expert knowledge. These data were put into an Access Database available on the project Microsoft SharePoint site. Habitat requirements included variables that species are adapted to that will be impacted by climate change, such as channel velocity, vegetation preference, and substrate type. For a complete list of variables considered, see Appendix B. These variables were compiled as categorical data and were transformed to a numeric dissimilarity matrix for use in clustering and ordination, using Gower distance (Gower 1971). Based on the habitat dissimilarity matrix, similar taxa were grouped using a hierarchical clustering method with six clusters of birds and six clusters combining fish, amphibians, and reptiles. Also based on the dissimilarity matrix, a non-metric multidimensional scaling (NMDS; Kruskal 1964) approach was used to show the distribution of the taxa in two-dimensional space. The NMDS and the clustering were done in tandem to compare the outcomes and confirm that species grouped in the cluster analysis occupy similar space in the ordination. There was overall high agreement between the two methods. All clustering and ordination tasks were completed in RStudio (RStudio Team 2016) with the package "cluster" (Maechler et al. 2017) and the package "vegan" (Oksanen et al. 2017).

Cluster adjustments were made based on comments from the technical advisory committee. Finalized clusters are shown in Appendix A; however, not all clusters were selected to have a representative species due to their lower dependence on stream habitat. For example, two clusters made up of fish, amphibians, and reptiles, plus four clusters of birds were not selected due to their more general reliance on aquatic habitats — a contrast to clusters of species that tend to be more stream specialists. This method allows for additional species to be added into a cluster if determined to be stream dependent.

During the second step, out of the 66 total species clustered, one or two focal species were selected from each group deemed riparian-dependent (Figure 7). The focal species(s) selected from each group represent archetypes that are expected to have similar responses to climate change-induced effects as the other group members. The focal species(s) selected have increased sensitivity to habitat fluctuations anticipated with climate change, are sensitive, and have high data availability needed for modeling. Fortunately, extremely sensitive species tend to be those with the largest collection of data. Seven focal species were selected from six clusters (one cluster had two species chosen). The focal species selected, along with a description of the habitat they represent, are shown in Table 3.



Figure 7: Focal species selection process following the cluster analysis.

Table 3: Groups formed by the cluster analysis and ordination. The representative species in each cluster has the qualities of being sensitive, native, and dependent on the riparian habitat. The cluster group refers to the clusters in Appendix A – note that not all clusters are represented.

Cluster	Description	Representative Species
2	Warm sluggish, shallow, backwater or main channel habitats of	Arroyo chub
3	Low to mid gradient stream Sucker: warm to cool flowing water with course substrate Turtle: Deep pools and warm water	Santa Ana sucker Western pond turtle
5	Cool, fast moving, higher gradient streams	Southern California steelhead/resident rainbow trout (<i>O. mykiss</i>)
6	Temporary shallow backwater pools in sandy substrate dependent on flooding to maintain habitat	Arroyo toad
8	Dense, 5-10 year successional stage, riparian vegetation dependent on flooding to maintain habitat	Least Bell's vireo
9	Shallow, slow, wide streams - represents the 'wading' birds	Great blue heron

OVERVIEW OF MODELING METHODS TO ASSESS ECOLOGICAL EFFECTS OF FLOW CHANGES

There are several approaches to model biological response to changes in flow and temperature, and to model hydrologic changes in response to changing climate conditions. The overall workflow is presented in Figure 9. For the species distribution modeling, there are a wide variety of specific models available that range from statistical relationships that relate occurrence and environmental conditions to mechanistic relationships based on life history needs (Table 4).



Figure 9: Work flow showing the levels of modeling beginning with species distributing modeling in specific modeled reaches through extrapolation of flow and temperature and species distribution to the entire region.

Table 4: Modeling techniques commonly used in the literature to predict ecological responses with the data input format. Rows in yellow indicate statistical models, blue rows are models based primarily on mechanistic approaches, and green represents a combination.

Modelling Technique	Description of Approach and Outputs	Model References
General Linear Model (GLM)	Relates probability of occurrence to flow or temperature based on linear regression with multiple possible relationships between the independent and the dependent variables	(McCullagh 1984; Venables and Dichmont 2004)
Multiple Linear Regression	A type of GLM that requires continuous data predictions (e.g., percent cover or abundance).	
General Additive Model (GAM)	A subset of the general linear model that is more adaptive and accounts for non-linear and non-parametric relationships, thus relying on smoothing functions of predictor variables	(Leathwick, Elith and Hastie 2006)
Logistic Regression	A type of GLM that calculates probability of occurrence based on measures of habitat suitability	
Classification and Regression Trees (CART)	Repetitively partitions the dependent data into homogenous groups nodes using regression principles resulting in a classification tree	(Breiman <i>et al.</i> 1984; Loh 2011)
Boosted Regression Trees (BRT)	Constructs an "ensemble" of regression trees (CART) and apportions sources of variability to different branches in the trees	(Elith, Leathwick and Hastie 2008)
Random Forest	A machine learning technique that generates many classification trees and aggregates the results to improve confidence in categories	(Prasad, Iverson and Liaw 2006)
Multivariate Adaptive Regression Splines (MARS)	Regression model allowing non-linear and non-parametric responses. Unlike the GAM, however, smoothing functions are not used and the final relationship consists of linear segments joined at inflection points	(Leathwick <i>et al.</i> 2005; Leathwick, Elith and Hastie 2006)
Genetic Algorithm for Rule- set Production (GARP)	Map of species distributions based on successive iterations of a rule-set, modified each time, to achieve convergence in a model solution	(Stockwell 1999)
Maximum Entropy Modeling (Maxent)	Probability of species occurrence based on Inferences from available data, avoiding unfounded constraints from the unknown (principles of maximum entropy)	(Phillips <i>et al.</i> 2006; Elith <i>et al.</i> 2011)
Environmental Envelope	Environmental range where presence can be applied to other locations in similar settings	
Functional relationship (HEC_EFM, IFIM)	Predicts time periods or conditions of likely species occurrence based on physical habitat requirements specific to a life stage	(Parasiewicz 2007)

Regression models use a series of predictor variables (in this case, environmental predictors) and an outcome dependent on those predictors. Depending on the relationship between the predictor and outcome variables, and the outcome data available to build the model, different regression techniques can be selected. Ideally, the most simplistic regression model is chosen that meets the criteria for the data.

The most simplistic statistical regression model is ordinary regression, which includes simple or multiple linear regression. These models relate a series of predictor variables (such as stream

velocity, water temperature) to a dependent variable (such as fish abundance). While easy to use, some of the assumptions make them poorly suited for species distribution modeling. For example, the assumption of normality is violated when the data are presence-only data because there is no variation in the dependent variable (i.e., in every case, the dependent variable equals "present"). Additionally, these ordinary regression models require a simple pattern between the predictor and outcome variables, such as a linear or quadratic relationship. These assumptions are relaxed with other regression techniques such as Generalized Linear Models (GLM; McCullagh 1984) that have an advantage when dealing with data with different error structures, particularly presence/absence data that are commonly available for spatial modelling of species distributions (Nicholls 1989, 1991, Rushton et al. 2004). Logistic regression is a type of GLM that predicts a dichotomous output and thus has application for predicting probability of presence under specific environmental settings.

Other types of regression analysis that further relax linear regression assumptions include generalized additive models (GAM), generalized additive mixed models (GAMM; Hastie and Tibshirani 1990, Yee and Mitchell 1991, Leathwick and Whitehead 2001), and multivariate adaptive regression splines (MARS; Friedman, 1991). MARS are sometimes preferred when there is a desire to use multiple predictors (Moisen and Frescino 2002; Muñoz and Felicisimo 2004). Leathwick et al. (2005) compared GAM and MARS methods for freshwater fish and concluded that although both methods were similar in terms of output, MARS had some computational advantages.

Machine learning methods are a statistical approach to species distribution modeling that use observed data to make rules about the patterns of species presence, rather than trying to fit the patterns to a parameterized distribution as is done in regression (Elith, Leathwick and Hastie, 2008). These techniques include classification (categorical response variable) and regression (continuous response variable) trees (CART; Breiman et al. 1984, Loh 2011), random forest, boosted regression trees (Elith, Leathwick and Hastie 2008), artificial neural networks (Hepner et al. 1990), and genetic algorithms for rule set production (GARP; Stockwell and Noble 1992), among others. MaxEnt is a variant of a machine learning approach developed to address the issue of presence only data (Phillips et al. 2006). MaxEnt uses only species presence data and an assortment of environmental variables to predict the probability distributions of likelihood of species presence given the environmental variables.

Friedman et al. (2000) compared BRT to GAM and concluded that BRT are better predictor models. In another study, Prasad, Iverson and Liaw (2006) compared various tree analyses to MARS and concluded that while MARS could predict current distributions, the trees were better for predicting future climate conditions. They determined the shortcomings of MARS were due to the localized nature of the predictor variables on the regression splines, which do not typically hold when the predictor variable range is expanded with new information, which is typical of climate change assessments.

Unlike regression and machine learning methods which start with large datasets and attempt to describe patterns, mechanistic models start with known habitat preferences derived from the literature. Models have been developed where habitat requirements are input into a program along with environmental time series, and then the likelihood of an environmental regime providing an appropriate habitat is determined. The most commonly used mechanistic model for assessing effects of instream flows on ecological communities is the Instream Flow Incremental

Methodology (IFIM), created by the U.S. Fish and Wildlife Service and the U.S. Geologic Survey specifically for assessing the ecological impacts of an altered flow regime. The associated models, PHABSIM and MesoHABSIM, use the IFIM approach based on detailed habitat information compiled and applied at a local scale. The Ecosystem Functions Model (HEC-EFM), available from the U.S. Army Corps or Engineer's Hydrologic Engineering Center, is another mechanistic approach created specifically for analyzing flow regime impacts on ecology (http://www.hec.usace.army.mil/software/hec-efm/). HEC-EFM uses information on species life-stage flow requirements to make inferences about impacts from a changing flow regime.

Considerations for model selection

Model selection depends on consideration of several factors such as a) desired spatial and temporal specificity and resolution of flow-ecology relationships, b) need to evaluate species vs. community level responses to changes in flow, and c) available data relative to input needs of the models. Each of these tradeoffs is discussed below, followed by a summary of attributes of available models (Table 5).

Spatial and temporal specificity of model output

Spatial and temporal specificity of modeled flow-ecology relationships is largely a function of the modeling approach used. Statistical or mechanistic approaches can be used to relate flow conditions to the likelihood of species (or specific life stages) occurring, and often a model combines characteristics of both approaches.

Statistical models relate species presence to specific environmental conditions (such as specific flow characteristics) using existing flow and biology data that have been concurrently collected. Statistical approaches can be used to develop relationships between physical and biological variables with known levels of confidence. Once these relationships are established, they can be used to assess how changes in the physical characteristics (e.g., flow) will relate to biological changes. Statistical models can be applied across broad spatial and temporal scales. However, they can only be extrapolated to areas represented by the data used to establish the statistical relationships. Appropriate training data must be used to apply statistical models to new areas or climate regimes. Although they can have wide geographic applicability, they are typically not spatially explicit (i.e., they relate to a region or type of stream rather than to a specific location). Unlike mechanistic models, statistical models imply correlation and not causation and are less easily manipulated to evaluate proposed management actions or changes over time. Meaningful statistical models rely on large, spatially representative data sets (i.e., high data density), but once developed, can be easily applied to the entire area or stream type covered by the input data. Common statistical models include generalized linear or additive models (e.g., GLMs or GAMs) or classification tree approaches (e.g., random forests or boosted regression trees; Table 4).

Mechanistic models, on the other hand, use well-studied relationships between a species and environmental variable(s) to predict how a change in the environment will impact specific lifehistory needs of the species. Results of mechanistic models can be used to connote causation more explicitly than statistical models. In general, mechanistic models are more spatially explicit (i.e., they can be used to predict ecological responses at specific locations) and are more appropriate for evaluating potential effects of management actions or changes over time. Because they are based on first principles derived from measured and theoretical relationships, they are more appropriate for assessing flow-ecology relationships within seasons, over different climatic patterns, or for different life stages. However, they are less easily generalizable across broad spatial scales, and application to a new location often requires collection of additional site-specific data and/or model calibration. Furthermore, these models often make simplifying assumptions based on the lack of complete knowledge of factors that control species distributions. For example, the observation that juvenile fish prefer riffles may be interpreted as a mechanistic connection between velocity, geomorphology and habitat preference. However, such preferences may also be behaviors intended to avoid predators, which may not be reflected in the model. Consequently, the underlying assumptions of mechanistic models must be viewed with caution. Commonly used mechanistic models include HEC-EFM and IFIM models. Several common approaches such as ELOHA and MaxEnt may use combinations of statistical and mechanistic approaches (Table 4).

Species vs. community level responses

Effects of changing flow (and temperature) patterns can be expressed at either the individual species or the biological community level. Species level responses can be modeled using either statistical or mechanistic approaches. Mechanistic models can be used to evaluate changes at either the behavioral/phenological or physiological level by accounting for changes in life-history requirements (Root et al. 2003, Walther 2004). Behavioral changes are often evaluated in response to changes in habitat suitability associated with changes in flow, temperature, or physical habitat conditions. For examples, amphibians (frogs) depend on temperature and precipitation to breed, or on spring precipitation events to form pools to lay eggs. Similar effects have been observed for fish larval activity in southern California (Asch 2015). It should be noted that although species-specific modeling focuses on responses for a given species, such responses by individual species are not isolated, but are also connected through interactions with other species at the same or adjacent trophic levels.

Community-level modeling combines data from multiple species and predicts collective biodiversity responses rather than individual species. Community-level modeling typically relies on statistical models that relate distributions of biological communities to habitat based on data from many species over broad geographies (Guisan and Zimmermann 2000, Rushton et al. 2004). Unlike species-level modelling, for which species with too little data are usually excluded from further analysis (for statistical reasons), many community-level modelling strategies make use of all available data across all species, regardless of the number of records per species. Hence, the data for more common species may help to support the modelling of less frequent species (Guisan et al. 1999). For example, GARP uses a set of point localities where the species is known to occur and a set of geographic layers representing the environmental parameters that might limit the species' capabilities to survive. GARP uses species presence and absence and environmental parameter values to build species prediction models. Using the new environmental conditions predicted by the climate change models, habitat suitability models can predict changes in the ecological niche and composition of biological communities (or populations) under changing conditions.

Ultimately, the choice of species vs. community modeling approaches is partly based on management priorities and partly based on data availability. However, if mechanistic models are desired, species-level responses are the more appropriate biological endpoint.

Availability of data

Use of statistically based species distribution modeling can be complicated by inconsistent and often biased data sources. Ideally, modelling is based on systematic survey data that document the presence or absence of a species, along with various environmental attributes, such as steam velocity and canopy cover. However, because much of the available data is based on single site visits, most often only presence data are available. While researchers have investigated modeling methods with presence-only data (Phillips et al. 2006, 2009) these methods fall short of being able to predict species prevalence due to the lack of knowledge about where a species is known *not* to occur (Hastie and Fithian 2013). When proper surveys are conducted, they can record simply the presence/absence or a species, or they can record the actual count of the species prevent. Therefore, availability of presence, absence, or count data will drive the model selection process.

Use of mechanistically based species distribution modeling is complicated by the difficulty of quantifying species habitat preferences. While detailed data exist for some species (typically sensitive or endangered species), data for other species are often sparse. Thus, use of mechanistic models is commonly limited by data documenting species' environmental tolerances.

Table 5: Summary of models available for use in assessing the relationship between changes in flow and changes in species occurrence

Modelling Approach	Summary	Data Requirements	Limitation	Output	Example
Regression Models					
Deterministic	Use species occurrence data and associated flow and temperature data to predict species abundance by weighting each predictor variable	 species or community abundance environmental characteristics 	 Need abundance or count data for model calibration 	 Species or community abundance Variable significance 	Linear Regression GLM/Poisson regression GAM MARS
Probabilistic	Use species occurrence data and associated flow and temperature data to predict probability of species occurrence by weighting each predictor variable	 species or community presence and absence environmental characteristics 	 Need presence and absence data for model calibration 	 Probability (or odds) of species or community presence Variable significance 	GLM/Logistic regression GAM MARS
Machine Learning Mode	els		-		
Tree Analysis	Machine-learning model that groups data by variables in order of importance	 species abundance or presence and absence environmental characteristics 	0	 Species or community abundance or probability (or odds) of species presence Variable significance 	Classification and regression Boosted Regression Random Forest K-nearest neighbor
Environmental Envelope	Predicts the probability of species distribution based on presence localities and environmental variable distributions	 Species presence Environmental characteristic's 	 Does not extrapolate well outside of training data ranges Assumes that presence locations represent the full extent of the species environmental tolerances 	 Map of probability of species occurrence in geographic space 	MaxENT

Modelling Approach	Summary	Data Requirements	Limitation	Output	Example
IFIM	Models instream habitats by accounting for hydraulic patterns and attributes that provide shelter at the micro (PHABSIM) or meso (MesoHABSIM) scale where fish spend a large portion of their time	 Seasonal and life stage species data Need depth, velocity and substrate cover measurements, during high, med, and low flow, in diverse types of reaches (glide, riffle, etc.) and in each season 	 Need detailed and specific fish and habitat data. Can't account for temperature or other environmental variables. Assumes habitat use represents behavioral selection 	 Calculates the weighted usable area (habitat) a species of fish in a certain life stage will be able to use under different discharges 	PHABSIM MESOHABSIM
Ecosystem Functions Model	Estimates positive or negative impacts of hydrologic alterations on ecologic parameters based on user defined relationships or species life stage requirements	 Daily time series of mean flow and stage Rules of species life stage and required flow needs 	 Need daily data. Can't account for temperature or other environmental variables 	 Flow and stage that meet ecological parameters 	HEC-EFM

Model selection flow charts

The choice of which model(s) to use should be based on the primary management questions being evaluated in consideration of the data/information available for the models being considered. For example, assessment of status of hydrologic "health" or future risk/vulnerability across an entire region may be best addressed through community-based statistical models. Evaluation of potential effects of water diversions on sensitive species or their habitats may be best addressed through a species rule-based mechanistic model. Figures 10 and 11 provide decision pathways for selecting models based management needs (Figure 9) and available data (Figure 11).



Figure 10: Model selection decision tree driven by management needs. Modeling type corresponds to those in Table 5.



Figure 11: Model selection decision tree driven by data availability. Modeling type corresponds to those in Table 4.

General consideration of flow and temperature requirements

Long-term survival and health of aquatic communities requires maintenance of flow and temperature patterns important for various life history needs. Understanding these needs is an important precursor to evaluating potential impacts associated with climate change, anthropogenic actions, or both.

Historically, the focus of ecohydrological analysis was on maintaining certain minimum instream flows. More recently, it has been widely agreed that other characteristics of the hydrograph are crucial for many riverine species (Petts 1996; Yarnell et al. 2015). The focus must be on all aspects of the hydrograph that are important for life cycle needs; for example, spring flooding is required for seed germination of the Fremont cottonwood (*P. fremontii*) and Godding willow (*S. gooddingii*) – two riparian vegetation species essential to the habitats of neotropical migratory birds (Stromberg 2001).

The natural flow paradigm, originally developed by Poff et al. (1997), states that ecological integrity is based on maintaining the natural dynamic flow regime of a river, described by six components: magnitude, frequency, duration, timing, rate of change, and overall variability of flow. Modification to the natural flow regime can adversely affect the organisms and communities that were assembled under the natural regime (Lytle and Poff 2004). The natural flow regime can be estimated based on historic (e.g., pre-disturbance) flow records (Richter et al. 1997a; Henriksen et al. 2006) or modelled using statistical associations or mechanistic models.

In some cases, it may be difficult or impossible to quantify and restore the natural flow regime of a river. In these cases, the designer flow paradigm can be considered (Acreman et al. 2014). The designer approach relies on the current state as the baseline and is forward-looking. The goal is to define and quantify attributes of the flow regime and assemble them into an environmental flow regime that meets desired ecological and social objectives (Acreman et al. 2014, Yarnell 2012, Olden 2017). In this way, rather than attempt to mimic a historical flow regime perfectly, we can focus in on the aspects of the flow regime that are important to biology and thus the hydrologic endpoints that are important to management.

Like flow attributes, there are thermal attributes that need to be met for ecological integrity. Also like flow, temperature can be affected by a combination of urbanization and climate change. Most of the temperature forecasting is done statistically using a synthesis of historical temperature trends to provide context (Kaushal et al. 2010). The effect of stressors varies spatially and temporally. For example, Nelson and Palmer (2007) showed using a combination of empirical relationships and modeling that headwater streams may be more pervasively impacted by urbanization than by climate change, although the two stressors reinforce each other. Seasonal temperature shifts and storms can be combined with a daily maximum water temperature model (Caissie et al. 1998, 2001) to estimate the probability of exceeding the critical thermal maxima under different scenarios (Figure 8).



Figure 8: Incorporating temperature fluctuation due to climate change

Functional flow metrics

Designing an environmental flow regime that adequately supports ecological function and aquatic biodiversity requires quantifiable metrics of hydrologic variability that directly relate to aquatic species response (Poff & Zimmerman 2010; Yarnell et al. 2016). Characteristics of a natural flow regime or a managed environmental flow can be described using several metrics, including the magnitude, frequency, duration, timing, and the rate of change in flow (Poff et al. 1997). However, determining which specific characteristics of the flow regime (e.g., magnitude or duration) drive various ecological responses of interest (e.g., BMI diversity or fish abundance) is often not clear.

For certain modelling approaches, relationships between flow metrics and ecological response are explicitly defined from data-driven field studies or analyses. For example, the foundation of the ELOHA method relies on mechanistic relationships between metrics of flow alteration and invertebrate community response, such that thresholds of ecologic integrity can be defined (Poff et al. 2010). In IFIM studies, field data on hydraulic habitat conditions and fish presence are used to create inferred relationships between flow discharge and habitat suitability (Bovee et al. 1998). In other modelling approaches, relationships between flow metrics and ecological response are implicitly defined by statistical relationships between quantifiable flow attributes and species indices. For example, Steel et al. (2017) found that duration of the spring flow recession is a strong indicator of benthic macroinvertebrate community diversity, with a steady increase in diversity as duration extended past 20 days. Depending on the ecological outcomes of interest and the choice of modeling methodology, resultant relationships between flow metrics and ecological response should be understood and evaluated in context.

Many studies relate various aspects of the flow regime to ecological outcomes; however, fewer studies have specifically evaluated individual quantifiable metrics with species response. For example, Stein et al. (2017) found that high flow duration, baseflow magnitude, and flow

variability (calculated as the interdecile range of flow) relate to benthic macroinvertebrate diversity in southern California streams, and Yarnell et al. (2016) found that the flow recession rate in springtime relates to success of amphibian breeding and rearing. Altered flow regimes have been quantified by comparison of metrics such as deviations in monthly and seasonal flows (Grantham et al. 2014) and magnitude of mean annual minimum flow (Carlisle et al. 2010). Specific flow metrics found to be important in these and other studies, however, may not be relevant to other streams, and/or may not relate to other species of interest. Therefore, it may be more useful in a regional analysis or in locations with limited site-specific data to quantify a set of flow metrics that relate to components of the flow regime that provide the greatest ecologic and geomorphic functionality.

A functional flows approach focuses on restoring specific flow components in an environmental flow regime that support natural disturbances, promote physical dynamics, and drive ecosystem functions (Yarnell et al. 2015; Figure 12). While streamflow has direct impacts on biota by providing water quantity and quality to support life history needs, it also directly impacts geomorphic conditions through erosion and deposition of sediments, and indirectly via connections with riparian and floodplain habitats that ultimately feed back into channel form and function. This interaction between flow, channel form, and ecological function is inherent to dynamic river systems. Therefore, based on the natural flow regime for most rivers in California, functional flows may include winter floods that drive geomorphic processes, spring recession flows and summer baseflows that support ecological processes, and wet season initiation flows that support biogeochemical processes. Restoration of these key flow components in an environmental flow regime will support the native species communities that have evolved over time in sync with the natural flow regime. Thus, focusing on specific metrics that quantify each key functional flow component will allow for design and monitoring of flow regimes that support the native species community, versus a single species of interest, and allow for transferability across streams with similar unimpaired flow characteristics.



Figure 12: Conceptual functional flow regions. Functional flow metrics are designed to ensure that the four key aspects of the annual hydrograph necessary to support species life histories are maintained.

Functional flow metrics for each of the four key functional flow components described in Yarnell et al. (2015) are listed in Table 5. The values for each metric can be determined from nearby reference gages or reference conditions for a similar type stream. Many of these metrics have also been shown to relate to particular ecological endpoints, such as invertebrate community diversity (e.g., spring flow duration (Steel et al. 2017), winter flood magnitude (Stein et al. 2017)), cottonwood germination (e.g., spring flow recession rate (Mahoney and Rood 1998)), amphibian breeding suitability (e.g., spring flow recession rate (Yarnell et al. 2016)), or salmonid spawning suitability (e.g., rate of change in flow (Moir et al. 2006)). Together, this suite of functional flow metrics quantifies the magnitude, timing, duration, frequency and rate of change of flows needed to support native communities in many California streams.

Functional Flow	Flow Characteristic	Flow Metric
Peak flood	magnitude	Q02 - 2% exceedance flow (50yr flood)
		Q05 – 20% exceedance flow (20yr flood)
		Q10 - 10% exceedance flow (10yr flood)
		Q20 – 20% exceedance flow (5yr flood)
		Q50 - 50% exceedance flow (2yr flood)
	timing	
	duration	# days - 100yr, 50yr, 10yr and 2yr floods
	frequency	# of 100yr, 50yr, 10yr and 2yr flood events in record
Spring transition	magnitude	flow at start (spring peak)
	rate of change	percent decrease per day
		avg change in flow per day
	timing	start date
	duration	# days (start-end)
Summer baseflow	magnitude	baseflow (10 th , 50 th , 90 th percentile)
	timing	start date (end date of spring transition)
	duration	# days (start-end)
	duration	# of no flow days
Fall/winter baseflow	magnitude	baseflow (10 th , 50 th , 90 th percentile)
Fall flush	magnitude	peak flush flow
	timing	start date
	duration	# days (start-end)

Table 5. Functional flow metrics used to quantify key functional flows as described in Ya	arnell et al.
2015.	

NEXT STEPS

Focal species have been selected and accepted by the Technical Advisory Committee. Once occurrence data for all the focal species has been compiled, we will refine the conceptual models of the life history of the focal species. For example, a description of functional flow or hydraulic conditions that are supportive or detrimental to each species ability to survive and reproduce are being compiled which will inform the environmental metrics used in the species distribution

modeling. These metrics will then be calculated from the reach level hydrologic modeling being done for this project based on current and future precipitation time series, but not all environmentally important metrics will be able to be calculated. The calculated metrics in conjunction with the species occurrence data will be used to build the predictive species distribution model.

These models will be used to estimate the probable current distribution of major groups of riparian-dependent species. During subsequent phases of the project, future rainfall and air temperature projections will be used to estimate changes in streamflow and water temperature, which in turn will be used to predict potential changes in distribution of the major classes of riparian-dependent species.

Many native riparian species of southern California have had populations decrease over the last century because of habitat destruction, harmful invasive species, and water quality deterioration. As the climate continues changing in response to increased atmospheric greenhouse gas concentrations, further habitat modification may occur as streamflow and stream temperature dynamics respond to new air temperatures and precipitation patterns. Only time will tell if our native freshwater fauna will be able to cope with these additional changes. However, by projecting the new species distributions under future conditions we can get an idea of the impacts and give managers time to plan. For example, reducing other harmful stressors like invasive species, water diversions, or relocating species to other suitable habitats may give species time to adapt to the new conditions. The outcome of this project will be a series of projected distributions of the seven focal species under the current and future climate scenarios to aid wildlife managers in their climate change preparation. The methodology and results will be published in future technical reports, but this report provides a detailed background and conceptual approach to the project.

LITERATURE CITED

Acreman, M., A.H Arthington, M.J. Colloff, C. Couch, N.D. Crossman, F. Dyer, I. Overton, C.A. Pollino, M.J. Stewardson, W. Young. 2014. Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. *Frontiers in Ecology and the Environment* 12(8): 466-473.

Asch, R.G. 2015. Climate change and decadal shifts in the phenology of larval fishes in the California Current ecosystem. *Proceedings of the National Academy of Sciences* 112(30):E4065-E4074.

Bellard, C., C. Bertelsmeier, P. Leadley, W. Thuiller, F. Courchamp. 2012. Impacts of climate change on the future of biodiversity. *Ecology letters* 15(4):365-377.

Bovee, K. D., B. L. Lamb, J. M. Bartholow, C. B. Stalnaker, J. Taylor, J. Henriksen. 1998. Stream habitat analysis using the Instream Flow Incremental Methodology. U.S. Geology Survey Biological Resources Division Information and Technology Report USGS/BRD-1998-0004.

Breiman, L., J.H. Friedman, R.A. Olson, C.J. Stone. 1984. *Classification and Regression Trees*. CRC Press.

Bunn, S.E. and A.H. Arthington. 2002. Basic principles and ecological consequences of altered flow regimes for aquatic biodiversity. *Environmental Management* 30(4):492-507.

Caissie, D., N. El-Jabi, M.G. Satish. 2001. Modelling of maximum daily water temperatures in a small stream using air temperatures. *Journal of Hydrology* 251(1):14-28.

Caissie, D., N. El-Jabi, A. St-Hilaire. 1998. Stochastic modelling of water temperatures in a small stream using air to water relations. *Canadian Journal of Civil Engineering* 25(2):250-260.

Carlisle, D.M., J. Falcone, D.M. Wolock, M.R. Meador, R.H. Norris. 2010. Predicting the natural flow regime: models for assessing hydrological alteration in streams. *River Research and Applications* 26(2):118-136.

Carlisle, D.M., D.M. Wolock, M.R. Meador. 2010b. Alteration of streamflow magnitudes and potential ecological consequences: a multiregional assessment. *Frontiers in Ecology and the Environment* 9:264-270.

Elith, J., J.R. Leathwick, T. Hastie. 2008. A working guide to boosted regression trees. *Journal of Animal Ecology* 77(4):802–813.

Elith, J., S.J. Phillips, T. Hastie, M. Dudik, Y.E. Chee, C.J. Yates. 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions* 17(1): 43–57.

Friedman, J.H.1991. Multivariate adaptive regression splines. The Annals of Statistics 1-67.

Friedman, N., M. Linial, I. Nachman, D. Pe'er. 2000. Using Bayesian networks to analyze expression data. *Journal of Computational Biology* 7(3-4):601-620.

Gower, J. C. 1971. A General Coefficient of Similarity and Some of Its Properties. *Biometrics* 27(4):857–871.

Graham, C.H., S. Ferrier, F. Huettman, C. Moritz, A.T. Peterson. 2004a. New developments in museum-based informatics and applications in biodiversity analysis. *Trends Ecol. Evol.* 19:497–503.

Grantham, T.E., J.H. Viers, P.B. Moyle. 2014. Systematic screening of dams for environmental flow assessment and implementation. *BioScience* 64:1006-1018.

Guisan, A. and N.E Zimmermann. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135(2):147-186.

Guisan, A., S.B. Weiss, A.D. Weiss. 1999. GLM versus CCA spatial modeling of plant species distribution. *Plant Ecology* 143(1):107-122.

Hastie, T. and W. Fithian. 2013. Inference from presence-only data; the ongoing controversy', *Ecography* 36(8):864–867.

Hastie, T. and R.J. Tibshirani. 1990. Generalized Additive Models. John Wiley & Sons, Inc.

Henriksen, J. A., J. Heasley, J. G. Kennen, S. Niewsand. 2006. Users' manual for the hydroecological integrity assessment process software: U.S. Geological Survey, Biological Resources Discipline, Open File Report 2006-1093. U.S. Geological Survey, Fort Collins, Colorado, USA

Hepner, G. F., T. Logan, N. Ritter, N. Bryant. 1990. Artificial Neural Network Classification Using a Minimal Training Set: Comparison to Conventional Supervised Classification. *Photogrammetric Engineering and Remote Sensing* 56(4):469–473.

Jetz, W., D.S. Wilcove, A.P. Dobson. 2007. Projected impacts of climate and land-use change on the global diversity of birds. *PLoS biology* 5(6):157.

Kaushal, S.S., G.E. Likens, N.A. Jaworski, M.L. Pace, A.M. Sides, D. Seekell, K.T. Belt, D.H. Secor, R.L. Wingate. 2010. Rising stream and river temperatures in the United States. *Frontiers in Ecology and the Environment* 8(9):461-466.

Kruskal, J. B. 1964. Nonmetric multidimensional scaling: A numerical method. *Psychometrika* 29(2):115–129.

Leathwick, J. R., J. Elith, T. Hastie. 2006. Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of species distributions. *Ecological Modelling* 199(2):188–196.

Leathwick, J.R., D. Rowe, J. Richardson, J. Elith, T. Hastie. 2005. Using multivariate adaptive regression splines to predict the distributions of New Zealand's freshwater diadromous fish. *Freshwater Biology* 50(12):2034-2052.

Loh, W.-Y. 2011. Classification and regression trees. WIREs 14–23.

Lytle, D.A. and N.L. Poff. 2004. Adaptation to natural flow regimes. *Trends in Ecology & Evolution* 19(2):94-100.

Maechler, M, P. Rousseeuw, A. Struyf, M. Hubert, K. Hornik, M. Studer, P. Roudier, J. Gonzalez. 2017. Package 'cluster'.

Mahoney, J.M., S.B. Rood. 1998. Streamflow requirements for cottonwood seedling recruitment - An integrative model. *Wetlands* 18:634-645.

McCullagh, P. 1984. Generalized linear models. *European Journal of Operational Research* 16(3):285–292.

McLaughlin, J.F., J.J. Hellmann, C.L. Boggs, P.R. Ehrlich. 2002. Climate change hastens population extinctions. *Proceedings of the National Academy of Sciences* 99(9):6070-6074.

Moir, H.J., C.N. Gibbins, C. Soulsby, J.H. Webb. 2006. Discharge and hydraulic interactions in contrasting channel morphologies and their influence on site utilization by spawning Atlantic salmon (*Salmo salar*). *Canadian Journal of Fisheries and Aquatic Sciences* 63:2567-2585.

Moisen, G.G. and T.S. Frescino. 2002. Comparing five modelling techniques for predicting forest characteristics. *Ecological Modelling* 157(2):209-225.

Muñoz, J. and Á.M Felicísimo. 2004. Comparison of statistical methods commonly used in predictive modelling. *Journal of Vegetation Science* 15(2):285-292.

Naiman, R.J., S.E. Bunn, C. Nilsson, G.E. Petts, G. Pinnay, L.C. Thompson. 2002. Legitimizing fluvial ecosystems as users of water—an overview. *Environmental Management* 30(4):455-467.

Nelson, K.C. and M.A. Palmer. 2007. Stream temperature surges under urbanization and climate change: data, models, and responses. *JAWRA Journal of the American Water Resources Association* 43(2):440-452.

Nicholls, A.O. 1989. How to make biological surveys go further with generalised linear models. *Biological Conservation* 50(1-4):51-75.

Nicholls, A.O. 1991. Examples of the use of generalized linear models in analysis of survey data for conservation evaluation. in: C.R. Margules, M.P. Austin (eds.), *Nature Conservation: Cost Effective Biological Surveys and Data Analysis* pp. 191-201. CSIRO. Melbourne, Australia.

Novak, R., J.G. Kennen, R.W. Abele, C.F. Baschon, D.M. Carlisle, L. Dlugolecki., J.E. Flotermersch, P. Ford, J. Fowler, R. Galer, L.P. Gordon, S.N. Hansen, B. Herbold, T.E. Johnson, J.M. Johnston, C.P. Konrad, B. Leamond, P.W. Seelbach. 2015. Draft: EPA-USGS Technical Report: Protecting Aquatic Life from Effects of Hydrologic Alteration: U.S. Geological Survey Scientific Investigations Report 2015–5160, U.S. Environmental Protection Agency EPA Report 822-P-15-002, XX p., http://pubs.usgs.gov/sir/2015/5160/ and http://www2.epa.gov/wqc/aquatic-life-ambient-water-quality-criteria

Oksanen, J., F.G. Blanchet, M. Friendly, R. Kindt, P. Legendre, D. McGlinn, P.R. Minchin, R.B. O'Hara, G.L. Simpson, P. Solymos, M. Henry, H. Stevens, E. Szoecs, H. Wagner. 2017. Community Ecology Package. http://cran.ism.ac.jp/web/packages/vegan/vegan.pdf.

Parasiewicz, P. 2007. The MesoHABSIM Model Revisited. *River Research and Applications* (23):893–903.

Petts, G.E. 1996. Water allocation to protect river ecosystems. *River Research and Applications* 12(4–5):353–365.

Phillips, S.B., R.P. Anderson, R.E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. *International Journal of Global Environmental Issues* 6(2–3):231–252.

Phillips, S.J., M. Dudik, J. Elith, C.H. Graham, A. Lehmann, J. Leathwick, S. Ferrier. 2009. Sample selection bias and presence-only distribution models: Implications for background and pseudo-absence data. *Ecological Applications* 19(1):181–197.

Poff, N.L. and J.K.H. Zimmerman. 2010. Ecological responses to altered flow regimes—A literature review to inform the science and management of environmental flows. *Freshwater Biology* 55(1):194–205.

Poff, N.L., J.D. Allan, M.B. Bain, J.R. Karr, K.L. Prestegaard, B.D. Richter, R.E. Sparks, J.C. Stromberg. 1997. The natural flow regime. *BioScience* 47(11):769-784.

Poff N.L., B.D. Richter, A.H. Arthington, S.E. Bunn, R.J. Naiman, E. Kendy, M. Acreman, C. Apse, B.P. Bledsoe, M.C. Freeman, J. Henriksen, R.B. Jacobson, J.G. Kennen, D.M. Merritt, J.H. O'Keefe, J.D. Olden, K. Rogers, R.E. Tharme, A. Warner. 2010. The ecological limits of hydrologic alteration (ELOHA): A new framework for developing regional environmental flow standards. *Freshwater Biology* 55: 147–170.

Poloczanska, E.S., S.J. Hawkins, A.J. Southward, M.T. Burrows. 2008. Modeling the response of populations of competing species to climate change. *Ecology* 89(11):3138-3149.

Prasad, A. M., L.R. Iverson, A. Liaw. 2006. Newer classification and regression tree techniques: Bagging and random forests for ecological prediction. *Ecosystems* 9(2):181–199.

Richter, B., J. Baumgartner, R. Wigington, D. Braun. 1997. How much water does a river need?. *Freshwater Biology* 37(1):231-249.

Root, T.L., J.T. Price, K.R. Hall, S.H. Schneider, C. Rosenzweig, J.A. Pounds. 2003. Fingerprints of global warming on wild animals and plants. *Nature* 421(6918):57-60.

RStudio Team. 2016. *RStudio: Integrated Development for R. RStudio, Inc.* Boston, MA. http://www.rstudio.com/.

Rushton, S.P., S.J. Ormerod, G. Kerby. 2004. New paradigms for modelling species distributions?. *Journal of Applied Ecology* 41(2):193-200.

Steel, A.E., R.A. Peek, R.A. Lusardi, S.M. Yarnell. 2017. Associating metrics of hydrologic variability with benthic macroinvertebrate communities in regulated and unregulated snowmelt-dominated rivers. *Freshwater Biology*.

Stein, E.D., R.D. Mazor, A. Sengupta, K. McCune, B. Bledsoe, S. Adams, S. Eberhart, M. Pyne, P. Ode, A. Rehn. 2017. Development of Recommended Flow Targets to Support Biological Integrity Based on Regional Flow-ecology Relationships for Benthic Macroinvertebrates in Southern California Streams. Technical Report 974. Southern California Coastal Water Research Project. Costa Mesa, CA.

Stockwell, D. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. *International Journal of Geographical Information Science* 13(2):143–158.

Stockwell, D. R. B. and I.R. Noble. 1992. Induction of sets of rules from animal distrubtion data: a robust and informative method of data analysis. *Mathematics and Computers in Simulation* 33:385–390.

Stromberg, J. C. 2001. Restoration of riparian vegetation in the south-western United States: importance of flow regimes and fluvial dynamism. *Journal of Arid Environments* 49:17–34.

Venables, W. N. and C.M. Dichmont. 2004. GLMs, GAMs and GLMMs: An overview of theory for applications in fisheries research. *Fisheries Research* 70(2–3 SPEC. ISS.):319–337.

Walther, B.A. and D.H. Clayton. 2004. Elaborate ornaments are costly to maintain: evidence for high maintenance handicaps. *Behavioral Ecology* 16(1):89-95.

Whitehead, D., J.R. Leathwick, A.S. Walcroft. 2001. Modeling annual carbon uptake for the indigenous forests of New Zealand. *Forest Science* 47(1):9-20.

Yarnell, S.M., A.J. Lind, J.F. Mount. 2012. Dynamic flow modelling of riverine amphibian habitat with application to regulated flow management. *River Research and Applications* 28(2):177-191.

Yarnell, S.M., G.E. Petts, J.C. Schmidt, A.A. Whipple, E.E. Beller, C.N. Dahm, P. Goodwin, J.H. Viers. 2015. Functional Flows in Modified Riverscapes: Hydrographs, Habitats and Opportunities. *Bioscience* 65:963-972.

Yarnell, S.M., R.A. Peek, G. Epke, A.J. Lind. 2016. Management of the Spring Snowmelt Recession in Regulated Systems. *Journal of the American Water Resources Association* 52:723-736.

Yee, T.W. and N.D. Mitchell. 1991. Generalized additive models in plant ecology. *Journal of Vegetation Science* 2(5):587-602.

APPENDICES

Appendix A: Documented taxa in the Los Angeles Regional Board area that are at least partially dependent on riverine/riparian habitats such as the Great Blue heron, or fully dependent on riverine/riparian habitats such as the American dipper. Species dependence on riverine/riparian habitats, listing as threatened or endangered, and origin are all listed followed by the cluster grouping. Bolded species are those chosen as focal species, and highlighted clusters are those that are represented. Note: additional species can be added in during future iterations.

Common name	Name	Group	Sensitive	Native	Cluster
African clawed frog	Xenopus laevis	Amphibian			1
American bullfrog	Lithobates catesbeianus	Amphibian		Y	1
Baja California treefrog	Pseudacris hypochondriaca hypochondriaca	Amphibian		Y	1
Western spadefoot	Spea hammondii	Amphibian	Y	Y	1
Red-eared slider	Trachemys scripta elegans	Reptile			1
Snapping turtle	Chelydra serpentina	Reptile			1
Western painted turtle	Chrysemys picta bellii	Reptile			1
Fathead minnow	Pimephales promelas	Fish			1
Golden shiner	Notemigonus crysoleucas	Fish			1
Western Mosquitofish	Gambusia affinis	Fish			1
Red shiner	Cyprinella lutrensis	Fish			1
Green Sunfish	Lepomis cyanellus	Fish			1
Two-striped garter snake	Thamnophis hammondii	Reptile		Y	2
Texas spiny softshell	Apalone spinifera emoryi	Reptile			2
Arroyo chub	Gila orcuttii	Fish	Y	Y	2
Threespine stickleback	Gasterosteus aculeatus	Fish	Y	Y	2
California treefrog	Pseudacris cadaverina	Amphibian		Y	3
California toad	Anaxyrus boreas halophilus	Amphibian		Y	3
Western pond turtle	Emys marmorata	Reptile		Y	3
Santa Ana sucker	Catostomus santaanae	Fish	Y	Y	3
California newt	Taricha torosa	Amphibian	Y	Y	3
California red-legged frog	Rana draytonii	Amphibian	Y	Y	3
Black bullhead	Ameiurus melas	Fish			4

Bluegill sunfish	Lepomis macrochirus	Fish			4
Brown bullhead	Ameiurus nebulosus	Fish			4
Largemouth bass	Micropterus salmoides	Fish			4
Tilapia spp	Oreochromis	Fish			4
Yellow bullhead	Ameiurus natalis	Fish			4
Common carp	Cyprinus carpio	Fish			4
Brown trout	Salmo trutta	Fish			5
Channel catfish	Ictalurus punctatus	Fish			5
Steelhead trout	Oncorhynchus mykiss	Fish	Y	Y	5
Santa Ana speckled dace	Rhinichthys osculus	Fish	Y	Y	5
Mountain yellow-legged frog	Rana muscosa	Amphibian	Y	Y	5
Arroyo toad	Anaxyrus californicus	Amphibian	Y	Y	6
California least tern	Sterna antillarum browni	Bird	Y	Y	7
Spotted sandpiper	Actitis macularius	Bird		Y	7
Black-necked stilt	Himantopus mexicanus	Bird		Υ	7
Bank swallow	Riparia riparia	Bird	Y	Y	8
Common yellowthroat	Geothlypis trichas	Bird		Υ	8
Least Bell's vireo	Vireo bellii pusillus	Bird	Y	Y	8
Lincoln's sparrow	Melospiza lincolnii	Bird		Υ	8
MacGillivray's warbler	Geothlypis tolmiei	Bird		Υ	8
Swainson's thrush	Catharus ustulatus	Bird		Υ	8
Willow flycatcher	Empidonax traillii	Bird	Y	Υ	8
Wilson's warbler	Cardellina pusilla	Bird		Υ	8
Yellow warbler	Setophaga petechia	Bird		Υ	8
Yellow-billed cuckoo	Coccyzus americanus	Bird	Y	Υ	8
Yellow-breasted chat	Icteria virens	Bird	Y	Υ	8
Black-crowned night heron	Nycticorax nycticorax	Bird		Y	9
Great blue heron	Ardea herodias	Bird		Y	9
Great egret	Ardea alba	Bird		Υ	9
Green heron	Butorides virescens	Bird		Y	9
Pied-billed grebe	Podilymbus podiceps	Bird		Y	9

Snowy egret	Egretta thula	Bird	Y	9
Wilson's snipe	Gillinago delicata	Bird	Y	9
Cinnamon teal	Anas cyanoptera	Bird	Y	10
Mallard	Anas platyrhynchos	Bird	Y	10
Northern pintail	Anas acuta	Bird	Y	10
Song sparrow	Melospiza melodia	Bird	Y	10
Wood Duck	Aix sponsa	Bird	Y	10
Brown-headed cow bird	Molothrus ater	Bird	Y	10
Cooper's hawk	Accipiter cooperii	Bird	Y	11
Long-eared owl	Asio otus	Bird	Y	11
Red-shouldered hawk	Buteo lineatus	Bird	Y	11
American dipper	Cinclus mexicanus	Bird	Y	12

Appendix B: Variables used in characterizing species habitats. The variables were selected as the most important for grouping species based on their habitat and flow related preferences. For definitions of categories and life history, see the associated Access database.

Life History	Categories
General habitat	Main channel, backwater, riparian, wetland, variable
Foraging behavior	Dabble, dive, fly, run, stalk, swim
Vegetation preference	Aquatic, overhanging, scrub, woodland, none
Prey preference (birds only)	Fruit, seed, grain, plant, fish, bird/mammal, terrestrial invertebrate, aerial invertebrate, aquatic invertebrate, amphibian
Water velocity	Fast, medium, slow, NA
Preferred substrate	Fine, sandy/gravel, cobble, boulder, NA
Nest location	Submerged substrate, emergent vegetation, nest at the bottom of a channel, cavity within a channel, ground, tree, shrub, bank, variable, NA
Stream category	Permanent, temporary, NA
Stream depth (fish and herps only)	Shallow, average, deep
Stream temperature (fish and herps only)	Cool, warm, hot